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Comparison of the Classifier Oriented Gait Score and the Gait Profile Score based on imitated gait impairments

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ABSTRACT

Common summary measures of gait quality such as the Gait Profile Score (GPS) are based on the principle of measuring a distance from the mean pattern of a healthy reference group in a gait pattern vector space. The recently introduced Classifier Oriented Gait Score (COGS) is a pathology specific score that measures this distance in a unique direction, which is indicated by a linear classifier. This approach has potentially improved the discriminatory power to detect subtle changes in gait patterns but does not incorporate a profile of interpretable sub-scores like the GPS. The main aims of this study were to extend the COGS by decomposing it into interpretable sub-scores as realized in the GPS and to compare the discriminative power of the GPS and COGS. Two types of gait impairments were imitated to enable a high level of control of the gait patterns. Imitated impairments were realized by restricting knee extension and inducing leg length discrepancy. The results showed increased discriminatory power of the COGS for differentiating diverse levels of impairment. Comparison of the GPS and COGS sub-scores and their ability to indicate changes in specific variables supports the validity of both scores. The COGS is an overall measure of gait quality with increased power to detect subtle changes in gait patterns and might be well suited for tracing the effect of a therapeutic treatment over time. The newly introduced sub-scores improved the interpretability of the COGS, which is helpful for practical applications.

1. Introduction

The abundance of data generated in instrumented gait analysis is an ongoing challenge in clinical applications and has provoked the development of summary measures of gait quality [1]. Such summary measures aim to extract a single number from various gait variables to represent an overall impression of the quality of a person's gait. Cimolin and Galli [1] reviewed the most commonly considered approaches in this domain: the Normalcy Index (NI) [2], the Gait Deviation Index (GDI) [3] and the Gait Profile Score (GPS) [4]. Regardless of the gait variables that constitute the feature space, these measures are based on the principle of measuring a distance of a person's gait pattern from the mean pattern of a healthy reference group. For that purpose various types of Euclidian distance measures have been used. For the NI, the Euclidian distance is squared whilst for the GDI, a logarithmic scaling is applied [2,3]. The GPS uses the root mean square difference, which essentially is a linearly scaled version of the Euclidian distance. The GPS focuses on interpretability and therefore avoids any additional scaling. It also avoids the principal component decomposition used in the NI and GDI to enhance interpretability. Moreover, it incorporates a decomposition of the GPS into sub-scores, which in the original work are referred to as Gait Variable Scores and are each associated with a specific joint angle. This decomposition is highly relevant for practical applications as it makes the GPS more comprehensible for the clinician by indicating the variables that contribute to its value. Therefore, the GPS can be linked to functional aspects of a gait pattern [4].

The recently introduced Classifier Oriented Gait Score (COGS) is an approach that is conceptually different from these summary measures of gait quality [5]. Like the other measures, the COGS quantifies how far a person's gait pattern differs from a healthy reference group. The specificity of this score is that the distance is measured along an axis in a specific direction determined by a linear classifier, which separates a group with a specific gait pathology from a healthy reference group. Therefore, the COGS is a pathology specific measure and a specially built COGS model is necessary for the evaluation of a specific gait pathology. The orientation of the COGS axis represents a weighting of each feature according to its contribution to separate the groups. Features that are less discriminatory are suppressed by assigning low classifier weights, while higher weights are given to stronger discriminatory features. The advantage of this approach is illustrated in Fig. 1,

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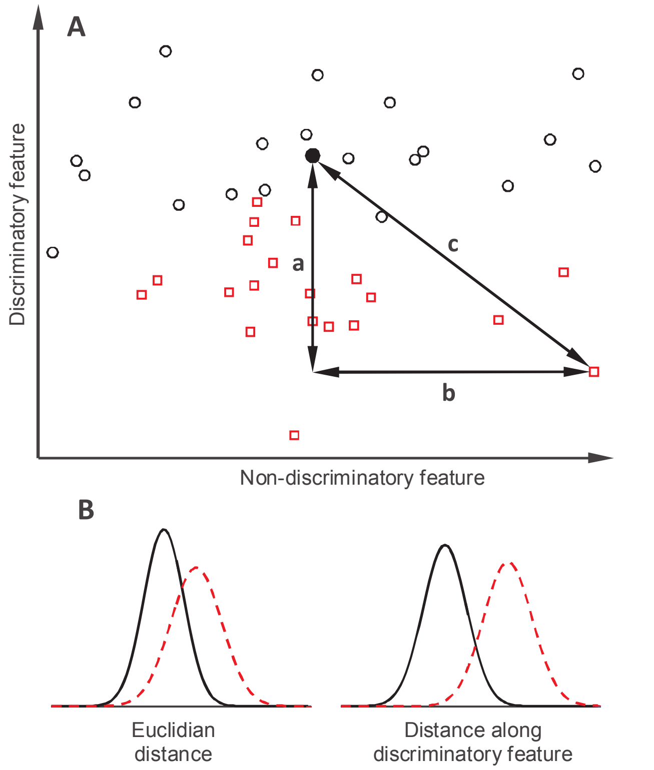

Fig. 1. Schematic example of distance measures in a 2-dimensional gait pattern vector space spanned by a discriminatory feature and non-discriminatory feature. A: The patterns of a healthy group (circles) and a group with gait pathology (squares) are depicted. For one example pattern three distance measures from the mean pattern of the reference group (filled circle) are indicated: distance along the discriminatory feature (a), distance along the non-discriminatory feature (b) and the Euclidian distance (c). B: Probability density functions of the healthy group (solid lines) and the pathologic group (dashed lines) for the Euclidian distance and the distance along the discriminatory feature.

which schematically shows that pathology has impact on the discriminatory feature, but not on the non-discriminatory feature (Fig. 1A). The overlap of the groups is greater with the Euclidian distance measure, while the distance along the discriminatory feature is better suited to differentiate the groups (Fig. 1B). The distance along the non-discriminatory feature is included into the calculation of the Euclidian distance and constitutes an additional source of non-informative variability leading to a reduction in group separation. In this example, the classifier would have a high weight on the discriminatory feature and a low weight on the non-discriminatory feature such that the COGS axis is oriented predominantly in the direction along the discriminatory feature. This makes the COGS a potentially more powerful method for detecting subtle changes in gait patterns compared with other methods that are based on the principle of measuring a Euclidian distance from the mean pattern of a healthy reference group [2–4]. The COGS, however, does not incorporate a profile of sub-scores like the GPS [4,5]. Decomposing the COGS into sub-scores could be useful to clarify its relation with functional aspects of the gait patterns and enhance its interpretability.

Consequently there were three aims in this study. The first aim was to extend the concept of the COGS with a profile of interpretable sub-scores similar to the GPS. The second aim was to compare the GPS and the COGS and their power of discriminating gait patterns associated with a specific type of impairment. The third aim was to validate the sub-scores of the GPS and the COGS and compare their ability to indicate functionally reasonable changes in the gait patterns.

2. Methods

2.1. General definition of the COGS based on [5]

Let $\boldsymbol{x}_v$ be a row vector of preprocessed discrete waveform data of a biomechanical gait variable (e.g. knee flexion angle) with samples x_t at T time points.

$$\boldsymbol{x}_v = [x_1\ x_2 \ldots x_t \ldots x_T] \tag{1}$$

Then $\boldsymbol{f}$ is the vector representation of a gait pattern resulting from concatenating equally sized waveform vectors of M variables with index v.

$$\boldsymbol{f} = [\boldsymbol{x}_1\ \boldsymbol{x}_2 \ldots \boldsymbol{x}_v \ldots \boldsymbol{x}_M] \tag{2}$$

The feature Matrix $\boldsymbol{F}$ is built by arranging the feature vectors of N participants from two gait pattern classes; the healthy class c^h and the pathologic class c^p.

$$\boldsymbol{F} = [\boldsymbol{f}_1^T\ \boldsymbol{f}_2^T \ldots \boldsymbol{f}_i^T \ldots \boldsymbol{f}_N^T]^T \tag{3}$$

Before fitting a classifier to the data, each column of $\boldsymbol{F}$ is z-transformed with the mean μ_j^h and standard deviation σ_j^h over a healthy reference group.

$$Z_{ij} = \frac{F_{ij} - \mu_j^h}{\sigma_j^h} \tag{4}$$

$$\boldsymbol{Z} = [\boldsymbol{z}_1^T\ \boldsymbol{z}_2^T \ldots \boldsymbol{z}_i^T \ldots \boldsymbol{z}_N^T]^T \tag{5}$$

This transformation ensures that the mean of the healthy reference group is the origin of the COGS axis and that each feature is scale independent. Then a weight vector $\boldsymbol{w}$ is computed by training a linear classifier function c to classify the patterns $\boldsymbol{z}$. $\boldsymbol{w}$ is a column vector with unit length ($\|\boldsymbol{w}\|_2 = 1$) that is orthogonal to the separating hyperplane with distance b from the origin.

$$c(\boldsymbol{z}) = \begin{cases} c^n & \text{for } \boldsymbol{z}\,\boldsymbol{w} + b \geq 0 \\ c^p & \text{for } \boldsymbol{z}\,\boldsymbol{w} + b < 0 \end{cases} \tag{6}$$

The raw COGS of a gait pattern is computed by projecting its z-transformed feature vector onto $\boldsymbol{w}$.

$$COGS^{raw} = \boldsymbol{z}\,\boldsymbol{w} \tag{7}$$

The raw score is scaled with a factor α to yield values from 0 to 10 between the mean raw score of the healthy reference group $COGS^{raw,h}$ and the mean raw score of the pathologic reference group $COGS^{raw,p}$.

$$COGS = COGS^{raw}\,\alpha \tag{8}$$

$$\alpha = \frac{COGS^{raw,h} - COGS^{raw,p}}{10} \tag{9}$$

2.2. Extension of the COGS by decomposing into sub-scores (Aim 1)

The COGS is decomposed into sub-scores, which are each associated with a specific biomechanical variable. An individual sub-score is calculated by first projecting $\boldsymbol{w}$ onto the subspace spanned by all features corresponding to a specific variable. This can be realized using a diagonal matrix $\boldsymbol{D}_v$ with all entries corresponding to the variable with index v set to one and all other entries set to zero.

$$\boldsymbol{w}_v = \boldsymbol{w}\,\boldsymbol{D}_v \tag{10}$$

$$\boldsymbol{D}_v = diag(\boldsymbol{d}_v) \tag{11}$$

$$\boldsymbol{d}_v = [d_1\ d_2 \ldots d_j \ldots d_{M\,T}] \tag{12}$$

$$d_j = \begin{cases} 1 & \text{for } (v-1)T + 1 \leq j \leq v\,T \\ 0 & \text{for all other } j \end{cases} \tag{13}$$

Projecting the z-transformed feature vector of a gait pattern onto $\boldsymbol{w}_v$ yields the raw sub-score.

$$COGS_v^{raw} = z\,\boldsymbol{w}_v \tag{14}$$

The sub-score $COGS_v$ is obtained by scaling the raw sub-score with α.

$$COGS_v = COGS_v^{raw}\alpha \tag{15}$$

The individual sub-scores sum up to the COGS.

$$COGS = \sum_{v=1}^{M} COGS_v \tag{16}$$

The relative weight w_v^{rel} of a variable can be computed by relating the 1-norm of $\boldsymbol{w}_v$ to the 1-norm of $\boldsymbol{w}$.

$$w_v^{rel} = \frac{\|\boldsymbol{w}_v\|_1}{\|\boldsymbol{w}\|_1} \tag{17}$$

2.3. Calculation of the GPS and sub-scores

The GPS was calculated as described previously [4]. First the sub-scores GPS_v are calculated for each biomechanical variable as the root mean square difference between a waveform $\boldsymbol{x}_v$ and the mean waveform of a healthy reference group $\boldsymbol{x}_v^n$.

$$GPS_v = \frac{1}{\sqrt{T}}\|\boldsymbol{x}_v - \boldsymbol{x}_v^n\|_2 \tag{18}$$

The GPS is then given as the root mean square average of its sub-scores.

$$GPS = \sqrt{\frac{1}{M}\sum_{v=1}^{M} GPS_v^2} \tag{19}$$

2.4. Participants

26 healthy male participants were recruited for this study (24 ± 3 yrs; 180 ± 5 cm; 77 ± 8 kg; all values mean ± standard deviation). All participants had no gait impairments, full range of motion in their lower extremity joints and all functional leg length discrepancies were smaller than 1.5 cm [6]. The study was approved by the institutional ethics board and written informed consent was obtained from all participants.

2.5. Imitation of gait impairments

To enable a high level of control while ensuring clear understanding of the functional aspects of the gait patterns, impairments were imitated by artificial disturbance of the normal gait. Impairments were imitated by restricting knee extension (RKE) or inducing a leg length discrepancy (LLD). Three levels of RKE were applied using adjustable orthoses: no restriction (RKE-0), 170° extension (RKE-1) and 140° extension (RKE-2). Three levels of LLD were applied by wearing shoes with different sole heights: equally soled (LLD-0), 2 cm difference (LLD-1) and 4 cm difference (LLD-2). The orthosis and the elevated soled shoe were applied on the right leg of all participants.

2.6. Experimental protocol and measurements

Gait analysis was performed on a laboratory walkway at self-paced walking speed. RKE and LLD were treated as separate independent conditions, hence, when the orthosis was applied, shoes with normal sole height were worn and when the modified shoes were worn, no orthosis was applied. Thus, each participant walked in six different conditions (RKE-0, RKE-1, RKE-2, LLD-0, LLD-1, LLD-2). 3D kinematic measurements were captured at 250 Hz.

2.7. Data analysis

The waveforms of a set of 15 variables (pelvic and hip angles in three planes, knee flexion, ankle flexion and foot progression) defined in Schwartz and Rozumalski [3] and also used in Baker, McGinley [4] was used to calculate the GPS and the COGS. The waveforms of one stride were time normalized to gain 51 data points over the full stride cycle [3,4]. The dataset was divided into two equally sized subsets for model training (N = 13) and testing (N = 13). Separate GPS and COGS models were trained for the RKE and LLD conditions. For training the GPS models, the healthy reference group was represented by the RKE-0 and LLD-0 conditions respectively (note no pathologic reference group was necessary). For training the GOGS models, the healthy reference group was represented by the RKE-0 and LLD-0 condition and the pathologic reference group was represented by the RKE-2 and LLD-2 conditions respectively. The training process consisted of calculating the mean waveforms of the healthy reference group $\boldsymbol{x}_v^n$ for the GPS models and the weight vector $\boldsymbol{w}$ for the COGS models. The weight vector $\boldsymbol{w}$ was determined using a linear support vector machine classifier with the penalization parameter C set to 1.

2.8. Comparing discriminating power of GPS and COGS (Aim 2)

Cohen's d within subject effect sizes and corresponding 95% confidence intervals were calculated for the GPS and COGS between all pairs of conditions [7]. The confidence intervals were computed using the bootstrap approach with 2000 iterations [8]. Differences between effects sizes were deemed significant with non-overlapping confidence intervals.

2.9. Comparison of the GPS and COGS sub-scores (Aim 3)

On the testing dataset, the GPS and COGS and their corresponding sub-scores were computed for all conditions and descriptively analyzed. Additionally, to enable more detailed interpretations of the COGS models the relative variable weights w_v^{rel} were determined.

3. Results

The GPS and the COGS from evaluating the testing dataset are depicted in Fig. 2. The difference between the RKE conditions and between the LLD conditions was generally larger for the COGS. This observation was evident in Fig. 3. The effect sizes between all pairs of conditions were significantly larger for the COGS.

Fig. 4 shows the GPS and COGS sub-scores for both conditions. For the RKE conditions both scores indicated a clear increase on the

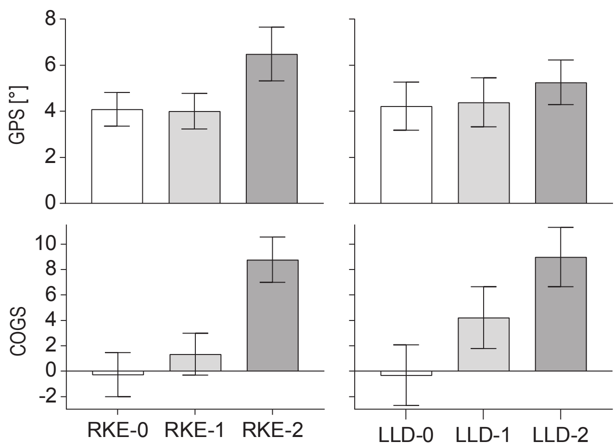

Fig. 2. Mean gait scores and standard deviations. Gait Profile Score (GPS) and Classifier Oriented Gait Score (COGS) for the three restricted knee extension (RKE) conditions (left) and for the three leg length discrepancy (LLD) conditions (right).

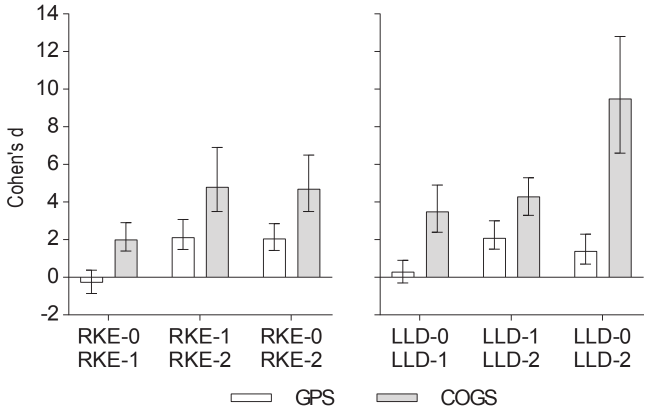

Fig. 3. Effect sizes and 95% confidence intervals of Gait Profile Score (GPS) and the Classifier Oriented Gait Score (COGS) between all pairs of restricted knee extension (RKE) conditions (left) and all pairs of leg length discrepancy (LLD) conditions (right).

variables right hip flexion, right knee flexion and right ankle flexion from the RKE-0 to the RKE-2 condition (Fig. 4A). For the LLD conditions both scores indicated a clear increase on the variable right ankle flexion from the LLD-0 to the LLD-2 condition (Fig. 4B). In Fig. 5 the relative variable weights of the two COGS models are illustrated. The dominant weight is put on the variable right knee flexion in the RKE model and on the variable right ankle flexion in the LLD model.

4. Discussion

The direct comparison of the COGS and the GPS showed improved discriminatory power of the COGS (Figs. 2 and 3). The COGS is a pathology specific measure that weights the features according to their contribution to discriminate the pathologic from healthy gait patterns [5] and the feature weighting is obtained by training a linear classification model. This approach has been previously applied on other high dimensional data such as magnetic resonance images using the linear support vector machine (e.g. [9,10]). The improved discriminatory power of the COGS can be advantageous, when for example, evaluating the outcome of a therapeutic treatment. Two

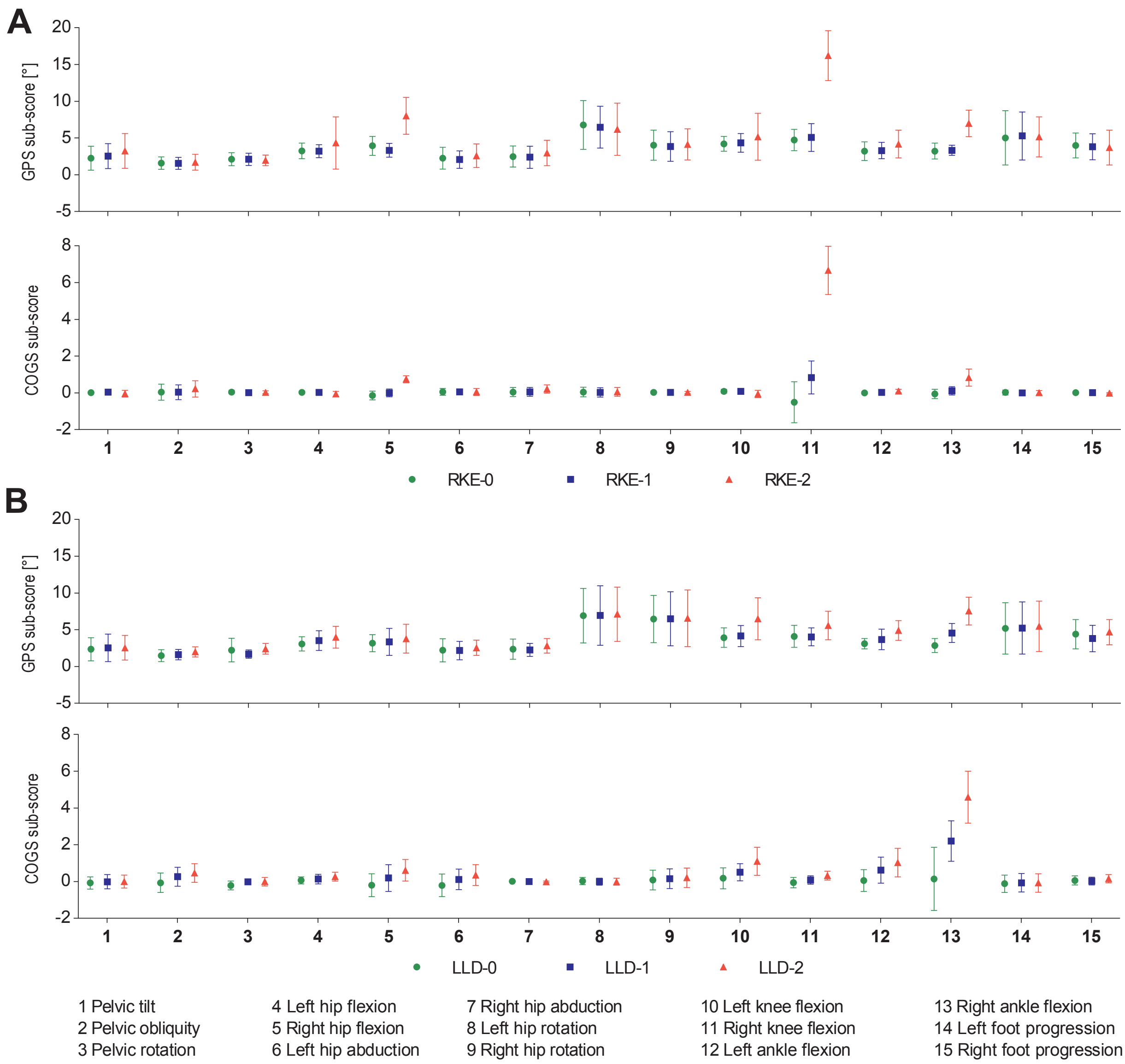

Fig. 4. Mean and standard deviations of the 15 sub scores of the Gait Profile Score (GPS) and the Classifier Oriented Gait Score (COGS). A: restricted knee extension (RKE) conditions. B: leg length discrepancy (LLD) conditions.

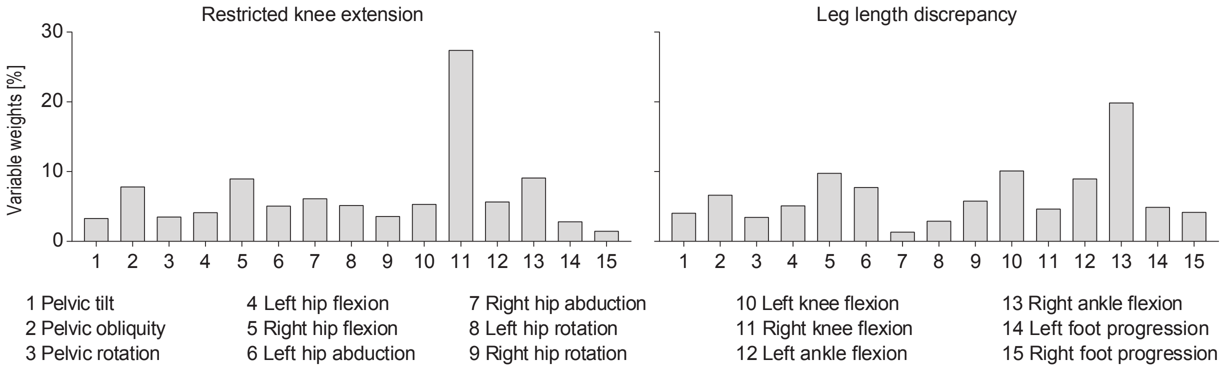

Fig. 5. Relative weights of the 15 biomechanical variables in the two COGS models.

levels of the imitated impairments could be considered as statuses before (e.g. RKE-1, LLD-1) and after (e.g. RKE-0, LLD-0) a therapeutic treatment respectively. The COGS would indicate a large effect of the treatment while the GPS is not sensitive enough to indicate any significant effect. This issue can be relevant when trying to establish a new type of treatment or when tracing the outcome of a treatment over time. The drawback, however, for the greater discriminatory power is the greater specificity of a COGS model. While the GPS can be applied to any type of impairment, a COGS model can only be applied to a specific type of impairment and the training process requires a reference group with this type of impairment additionally to the healthy reference group. This issue also addresses the laterality of the impairment, so if a COGS model is trained for a knee injury (e.g. ACL-rupture) it might involve an injury of either the left or the right knee. This can be solved by changing the definition of body sides from “left/right” to “affected/unaffected” [5].

The GPS can have greater discriminatory power on an individual sub-score compared with the overall GPS. This becomes visible for example for the GPS sub-score of variable 13 for the LLD impairment (Fig. 4B). The scores for the LLD-0 and LLD-1 conditions have less overlap compared with the overall GPS (Fig. 2 top right). This is because the ratio between discriminatory and non-discriminatory dimensions can be greater for an individual sub-score than for the overall GPS. Any additional non-discriminatory features can reduce the degree of separability. Therefore the GPS is not robust for the selection of variables while the COGS can handle the presence of non-discriminatory dimensions more effectively by assigning low weights. Furthermore, the GPS represents a root mean square average of its sub-scores, therefore a high value on a specific variable can be averaged out by low values on other variables [11]. By contrast, the COGS is simply the sum of its sub-scores and is thus not affected by this issue.

The GPS does not apply any scaling on the data, so the score is physically interpretable and the original units remain (degrees). This becomes problematic if the score should be extended with additional variables on a different scale such as joint moments or muscular activities as suggested by Cimolin and Galli [1] because variables on a larger scale would dominate the score in this case [2]. For this reason, the COGS was presented including a z-transform of the features and can be applied to all types of biomechanical waveform data. It should be noted that even if the variables have the same units like in this study the z-transform puts relatively more weight on joint angles with smaller range of motion (e.g. pelvic angles) compared to those with larger range of motion (e.g. knee angle). Potentially this is advantageous for detecting differences in smaller range of motion joint angles. However, the imitated pathologies affected mostly larger range of motion joint angles such as the knee and ankle joint so no significant advantage could be observed in the current study. An overweighting of unaffected variables has not been observed as discussed in more detail below. The physical meaning of the COGS is defined by the clinical status of the healthy and the pathologic reference groups. Values around zero are associated with healthy gait, while values around ten are associated with a gait pattern similar to the pathologic reference group. For interpreting the score, the distribution of the score of the reference groups should also be considered.

The sub-scores of the GPS and the COGS indicated the dominant changes between conditions for the same variables (Fig. 4). These were the hip flexion angle, the knee flexion angle and the ankle flexion angle for RKE. For this impairment, it was expected that the right knee flexion angle would be most affected since the orthosis directly restricted the motion in the knee joint. Large effects were also expected on the right hip flexion and right ankle flexion angle since the hip and ankle joints are adjacent to the knee joint and thus have to compensate most for its restricted mobility. For the LLD impairment, both scores indicated the dominant change of their sub-scores on the right ankle flexion angle. This is also reasonable from a functional viewpoint, as the right ankle is the joint directly linking the right foot, which was equipped with the thicker soled shoe. Since the sub-scores of the GPS and the COGS indicated the dominant changes on the same variables and these variables are functionally reasonable the results supports the validity of both approaches. The relative feature weights of the COGS models reasonably reflect the functional considerations by assigning the largest weight on the knee flexion angle for the RKE impairment and on the ankle flexion angle for the LLD impairment (Fig. 5). It should be noted that the feature weighting leads to a scaling of the COGS variances. For example hip rotation or foot progression show high variance in the GPS sub-scores but not in the COGS sub-scores. These angles have high inter-individual variability providing weak discriminatory power. Therefore the COGS is weighting these variables with small values making the variance to appear smaller. The opposite can be observed when variables are highly weighted as for example ankle flexion for the LLD impairment (Fig. 4).

The imitation design facilitated the impairments in a well-controlled manner. Imitations of gait impairments have also been used in previous studies to enable a high level of movement control (e.g. [12–14]), therefore it was a foregone conclusion that the impairments have an effect on the gait kinematics. With this certainty of an actual effect, it was possible to compare the gait score models on their ability to detect and quantify this effect. Furthermore, the imitations enabled a clear understanding of which variables were affected predominantly by the impairments, thereby validating the corresponding sub-scores.

The imitation design resulted in considerably homogeneous gait impairments. For real impairments it is likely that the pathologic patterns were more heterogeneous and this might affect the performance of a COGS model. The generalization to real impairments remains restricted in this context.

5. Conclusions

This study introduced a decomposition of the COGS into sub-scores and a comparison of the GPS with the COGS for evaluating imitated impaired gait patterns. It was shown that the COGS increased discriminatory power on a specific type of impairment, but in contrast to the GPS, it requires a group with this type of impairment as a reference in addition to a healthy reference group. The sub-scores of the GPS and the COGS detected the changes that were expected for the corresponding types of impairments and the validity of both scores was confirmed. The COGS might be a favored option in clinical settings where a specific type of impairment is treated predominantly, for example for evaluating the functional outcome of hip or knee surgeries.

Conflict of interest statement

None of the authors had any financial or personal conflict of interest with regard to this study.

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